IIE Transactions (2007) **39**, 57–71

ISSN: 0740-817X print / 1545-8830 online
DOI: 10.1080/07408170600940005

Toward modeling and simulation of critical national infrastructure interdependencies

HYEUNG-SIK J. MIN[1], WALTER BEYELER[1], THERESA BROWN[1], YOUNG JUN SON[2,*] and ALBERT T. JONES[3]

[1]*Sandia National Laboratories, Albuquerque, NM 87185, USA*
[2]*Systems and Industrial Engineering, University of Arizona, Tucson, AZ 85721-0020, USA*
E-mail: son@arizona.edu
[3]*Manufacturing Systems Integration Division, NIST, Gaithersburg, MD 20899, USA*

Received April 2005 and accepted October 2005

Modern society's physical health depends vitally upon a number of real, interdependent, critical infrastructure networks that deliver power, petroleum, natural gas, water, and communications. Its economic health depends on a number of other infrastructure networks, some virtual and some real, that link residences, industries, commercial sectors, and transportation sectors. The continued prosperity and national security of the US depends on our ability to understand the vulnerabilities of and analyze the performance of both the individual infrastructures and the entire interconnected system of infrastructures. Only then can we respond to potential disruptions in a timely and effective manner. Collaborative efforts among Sandia, other government agencies, private industry, and academia have resulted in realistic models for many of the individual component infrastructures. In this paper, we propose an innovative modeling and analysis framework to study the entire system of physical and economic infrastructures. That framework uses the existing individual models together with system dynamics, functional models, and nonlinear optimization algorithms. We describe this framework and demonstrate its potential use to analyze, and propose a response for, a hypothetical disruption.

Keywords: System dynamics, IDEF, critical infrastructure, disruption evaluation

1. Introduction

The continued prosperity and national security of the US is dependent on the reliable operation of a complex network of interdependent, large-scale, critical infrastructures. The impact of disruptions, deliberate or accidental, can be devastating[1]. Therefore, our ability to model and analyze the behavior of these infrastructures, individually and collectively, is of critical importance. Building the models and doing the analysis, however, is challenging because: (i) data acquisition is difficult; (ii) each individual infrastructure is complicated; (iii) infrastructures are evolving; (iv) governing regulations are changing; and (v) model construction is jointly performed by government agencies, academia, and private industries. Nevertheless, models have been built for a number of individual infrastructures including power, petroleum, natural gas, water, transportation, and communications.

The National Infrastructure Simulation and Analysis Center[2] was initiated in 1999 to understand the potential consequences of infrastructure interdependencies. Participants seek to develop modeling and analysis tools that can capture those independencies, evaluate the potential effects of disruptions in one infrastructure on all the others, and suggest strategies to mitigate these effects. The successes include a modeling framework based on system dynamics and IDEFØ, and a decision support tool based on nonlinear optimization algorithms. In this paper, we describe these results and show how we applied them to an example disaster scenario.

The remaining sections are organized as follows. In Section 2, we discuss definitions, scope, and issues of critical infrastructures. In Section 3, we provide an overview of the techniques and methodologies used in this research. In Section 4, we provide details of modeling critical infrastructure interdependencies using system dynamic simulation

*Corresponding author
[1]The economic impacts of recent Internet worms and power outages are in the billions of dollars.

[2]The National Infrastructure Simulation and Analysis Center is a joint program at Sandia National Laboratories and Los Alamos National Laboratory, funded and managed by the Department of Homeland Security's (DHS) Preparedness Directorate.

and nonlinear optimization techniques under disruptions. In Section 5, we examine experimental results and in Section 6 we give conclusions.

2. Interdependencies of critical infrastructures and their protection

In this section, we discuss definitions, significance, classification, and capturing of interdependencies of critical infrastructures.

2.1. *Definition and significance of critical infrastructures*

The US Critical Infrastructure Assurance Office defines an infrastructure as "the framework of interdependent networks and systems comprising identifiable industries, institutions (including people and procedures), and distribution capabilities that provide a reliable flow of products and services essential to the defense and economic security of the U.S., the smooth functioning of governments at all levels, and society as a whole" (Presidential Decision Directive 63, 1998). From this perspective, infrastructures include agriculture/food, drinking water, banking and finance, chemical industry and hazardous materials, defense industrial base, public health, emergency services, energy, government, information and telecommunications, and transportation. After September 11th, other key additions were made including national monuments and icons, postal and shipping and other specific types of infrastructure, public and commercial assets (Anon, 2003).

Deliberate attacks or serious accidental failures of one infrastructure may result in regional or even national consequences because of the potential for cascading effects across other infrastructures. For example, consider the recent power outage in August 2003. Traffic lights went out, computer systems went off, subway and other trains did not run, businesses and banks had to close, stock exchanges closed, health care facilities had to run on emergency power or close, sporting events were cancelled, and schools closed early, among other things. More importantly, these problems occurred in several major places such as New York, Michigan, Ohio, Pennsylvania, and Canada.

2.2. *Classifying and capturing interdependencies*

Rinaldi *et al.* (2001) classified infrastructure interdependencies as being one of four types: physical, cyber, geographic or logical. Physical interdependency means that the physical output of one infrastructure is the physical input to another infrastructure. In this type of interdependency, perturbations in one infrastructure will impact the other. Therefore, the risk of failure or deviation from normal operating conditions in one infrastructure will be a function of risk in the other infrastructure. Cyber interdependencies occur due to infrastructures being connected via information links. Cyber interdependencies are relatively new and are a result of advanced computerization and networking. Disruptions in one infrastructure may or may not cause disruptions in another infrastructure, depending on the nature and magnitude of the disruption. Geographical interdependency means that two infrastructures impact one another because of physical proximity. Events such as an explosion or a fire could create correlated disturbances in these geographically interdependent infrastructures. However, the state of one infrastructure usually does not affect the state of the other infrastructures. Logical interdependency means that the state of one infrastructure depends on the state of another infrastructure, usually via human decisions and actions. For example, a lower gas price increases the flow of gasoline and traffic congestion. In this case, the logical interdependency between the petroleum and transportation infrastructures is due to human decisions and actions and is not the result of a physical process.

Simulations and other models exist for all of the individual infrastructures we include in this study. Each model has its own assumptions, data requirements, time units, scaling factors and computational algorithms. Each model has its own objective function(s); for example, meeting service goals with the minimum number of communication links, maximizing the probability of making successful or securing banking transactions. Furthermore, these individual models do not capture emergent behavior, a key element of interdependency analysis. Therefore, we conducted a study to determine how to map between various data formats and to convert timing requirements. Dealing with multiple objective functions is more difficult, because they conflict with one another and, consequently, cannot be satisfied simultaneously. In this work, we developed a global objective function to minimize the impact of disruptions on the whole society (see Section 4).

3. Overview of proposed methodologies

In this section, we give an overview of the three major methodologies used in this research: (i) system dynamics; (ii) the IDEFØ functional-modeling technique; and (iii) nonlinear optimization.

3.1. *System dynamics*

We used a System Dynamic (SD) approach to develop our model of the entire system. This approach, developed initially from the work of Forrester (1961) and extended by Sterman (2000), provides a methodology to study and manage complex feedback systems. Stocks (the accumulation of resources in a system), flows (the rates of change that alter those resources), and feedback are the central concepts in this methodology. Simulations based on this methodology can provide insight into important causes and effects, which can lead to a better understanding of the dynamic and evolutionary behavior of a system.

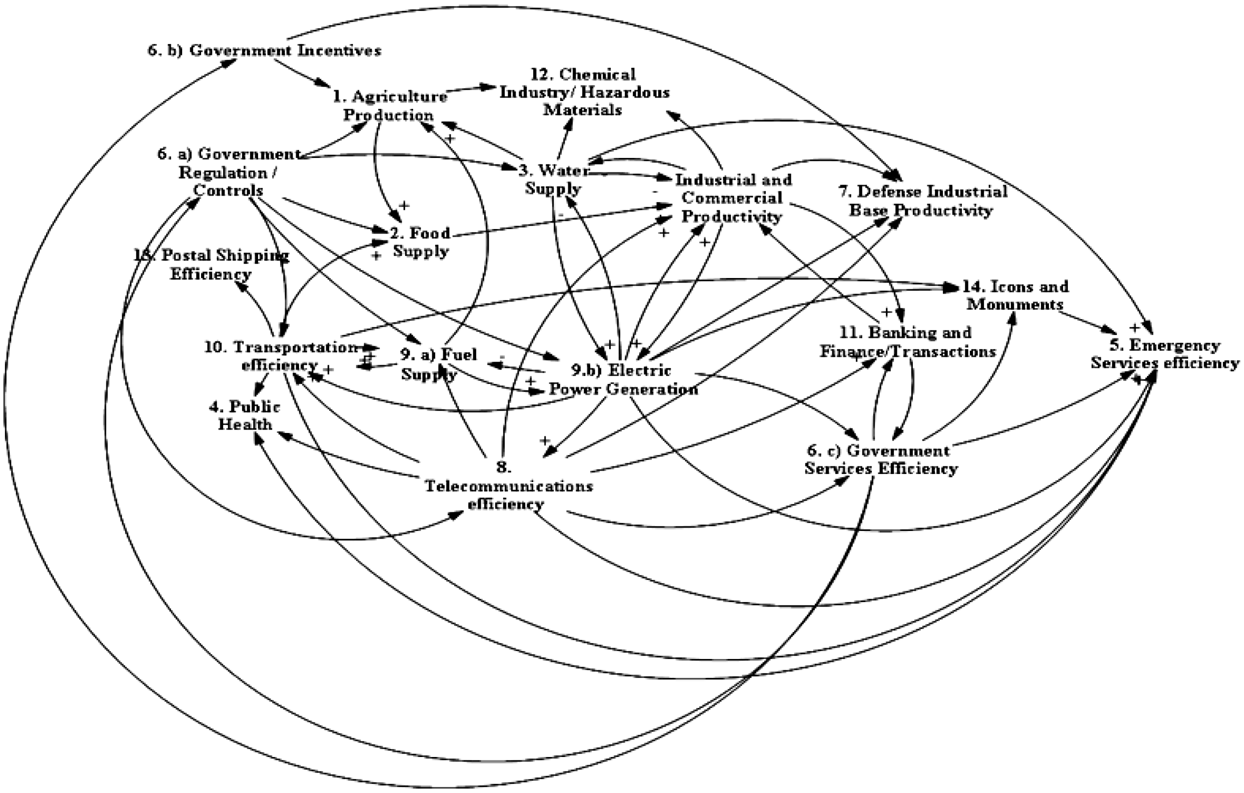

Fig. 1. Infrastructure interdependency.

Two diagrams are used to capture the structure of systems: (i) causal-loop diagrams; and (ii) stock-and-flow diagrams. A causal-loop diagram consists of variables connected by arrows; it captures the causal influence among the variables. Each loop has an associated identifier, which shows whether the loop is positive (reinforcing) or negative (balancing) feedback. The causal-loop diagram provides a high-level view of relationships, interactions, and feedback processes. Consequently, it is hard to see the physical buildup and flow of information and products through the system. For this, we need stock-and-flow diagrams, which consist of stocks (integrals or state variables), flows (derivatives or rates), valves (controlling the flows), and clouds (sources and sinks for the flows). The stock-and-flow diagrams can be used to generate the differential equations that govern the evolution of the system. The modelers can start with either of the diagrams (which complement each other) to build a SD model.

In this work, we started with the causal-loop diagram to capture the strengths of major interactions between each of the infrastructures (see Fig. 1). To build a causal-loop diagram, we identified the major variables that directly influence one another and connect them with a directional arrow. Each arrow was then assigned a "+" or "−" sign. A "+" sign means that changes in the first variable cause changes "in the same direction" in the second variable. A "−" sign means that changes in the first variable cause a change "in the opposite direction" in the second variable. The behavior of the entire infrastructure system is the result of the complex interrelationships among the various system variables. From these causal-loop diagrams, we developed stock-and-flow diagrams (Richardson, 1986, 1997; Sterman, 2000; Binder *et al.*, 2004), from which we derived a qualitative description of the mathematical relationships between the variables (see Fig. 5 for an example). Using data from the real world, we then wrote down the exact equations, which formed the basis for our simulations. These simulations can take randomness into account and provide an experimentation capability that is not possible in the real world. They also provide the basis for the stability analysis needed to understand the impact of disturbances (see Sections 4 and 5 for an example).

3.2. *IDEFØ*

We used a common, functional-modeling technique (IDEFØ) to help define data requirements and describe the exchange of information between the individual simulation models (see Figs. 2 and 3). IDEFØ diagrams[3] provide unambiguous guidelines that facilitate the development of large-scale, networked, computer-based models that behave consistently and correctly. The hierarchical

[3]Please consult http://www.idef.com for a discussion on these diagrams.

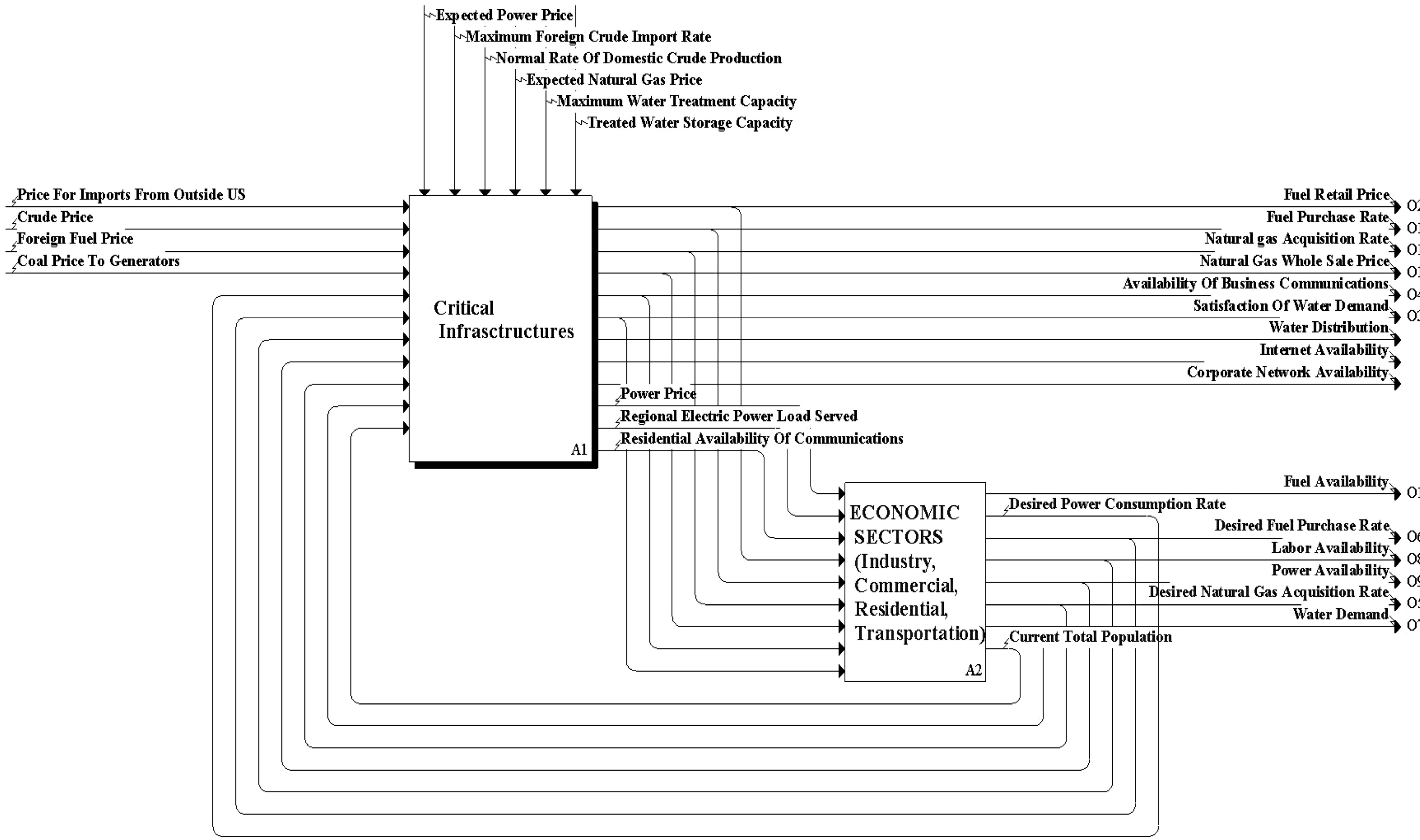

Fig. 2. IDEFØ diagram of the interdependency model of the critical infrastructures and economic sectors.

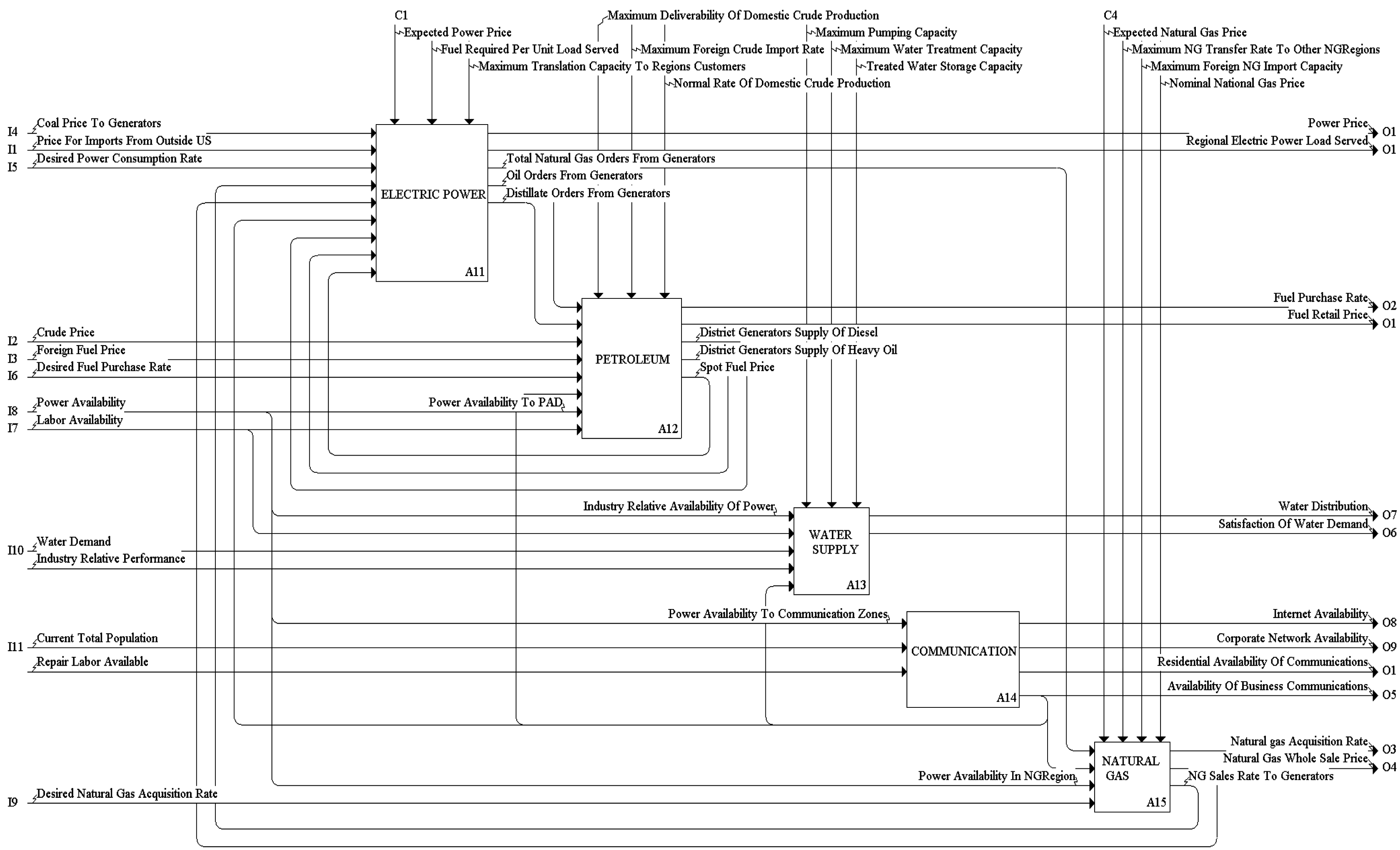

Fig. 3. IDEFØ diagram of the interdependency model of the critical infrastructures.

nature of IDEFØ, another strength of the method, facilitates the ability to construct ever-more detailed models that have both top-down and bottom-up features. The representation and interpretation are top down; the analysis building processes are bottom up.

Modeling efforts in this research consider over 5000 variables and parameters, and therefore, we significantly benefit from the hierarchical nature of IDEF. Figure 2 shows the top level of this hierarchy. In Fig. 2, there is one box for the critical infrastructure and one box for the economic model infrastructure. The arrows going into and out of each box represents the major interdependencies in terms of both physical and information flows. Arrows entering on the left side of the box are the inputs; arrows entering the top of the box are the controls; arrows entering the bottom of the box are the mechanisms; and the arrows leaving the box on the right side are the outputs of the function. Figure 3 shows the next detail level of A1: critical infrastructures including one box for each of the critical infrastructures.

3.3. *Nonlinear optimization*

Once the integrative SD model of the critical infrastructure is constructed, we need to find the values for the control variables such that an expected system performance from the SD simulation is optimized. In this work, the objective function is to maximize total economic revenue in the case of disruptions (for more details see Section 4.1). Contemporary simulation optimization methods (Azadivar and Tompkins 1999) include: (i) gradient-based search methods; (ii) stochastic approximation methods; (iii) sample path optimization; (iv) response surface methods; and (v) meta-heuristic search methods, including genetic algorithms, simulated annealing, and tabu search. In this work, we employ a suite of nonlinear optimization algorithms, which is combined into a MINOS software package (Murtagh and Sanders, 1998), since it is widely known and available. In MINOS, problems with linear constraints and nonlinear objectives are solved using a reduced-gradient algorithm (Wolfe, 1962) in conjunction with a quasi-Newton algorithm (Davidon, 1959). On the other hand, problems that contain nonlinear constraints are solved with a Lagrangian algorithm based on a method due to Robinson (1972). To overcome the problems of local optima, we start the optimizer in a number of different places.

4. Interdependency model of the critical infrastructures and the optimization problem

The main purpose in building an integrated interdependency model of the critical infrastructures is to simulate the effects of localized capacity losses on the entire integrated system. Each infrastructure model includes the available capacity for the supply side of the system (production and transportation process) as a function of the maximum production capacity and reductions in that capacity due to damage to the physical system or shortages of essential inputs, which come from other infrastructures. The simulations are driven by historical, time-series data that include diurnal and seasonal variations in demand. Prices are modeled as a function of the ratio of supply to demand and include demand elasticity functions that alter the demand in response to price. In this section, we provide details of modeling critical infrastructure interdependencies using SD simulation and nonlinear optimization techniques.

4.1. *Problem definition and model description*

In this study, we used the SD simulation to determine how best to allocate available infrastructure services or materials to physical infrastructures and to economic sectors under disruption. We did this by minimizing the potential economic impacts and by investigating scenarios with various magnitudes, dispersion, and duration of disruptions. The notation we used to do this is shown below.

Notation:

L_i = capacity loss of critical infrastructure i;
CI_i = total available products/services of critical infrastructure i;
α_{ij} = satisfaction rate of desired consumption of product/service i for demand sector j;
D_{ij} = desired consumption of product/service i for demand sector j;
I_{ij} = available inventory of product/service i for demand sector j;
ER_j = economic revenues of demand sector j;
R_{ij} = relative availability of product/service i for sector j;
LA = labor availability;
AP_{ij} = allocated product/service i for demand sector j;
i = p(power), f(fuel), g(natural gas), w(drinking water), c(communication);
j = R(residential), C(commercial), I(industrial), T(transportation).

Our objective function is to find optimal α_{ij} to maximize total economic revenue $TER = \sum ER_i$, during a disruption of a certain infrastructure i. Economic revenue ER_i is the cumulative difference between income I_i and expenditures S_i in sector i over the model period [0, T]:

$$ER_i = \int_0^T (I_i - S_i)\,\mathrm{d}t. \tag{1}$$

Residential sector income is from wages, while income in the remaining sectors arises from output purchased by other sectors. Expenditures are divided into purchases of generic goods and services from other sectors, and purchase of infrastructure services such as electric power and fuel. Infrastructure service purchases are distinguished from generic commercial and industrial output because the specific technical factors influencing production and consumption are the focus of the model. No distinction is made between capital purchases (investment) and operating expenses in the commercial and industrial sectors. The purchasing rate for both generic goods and infrastructure output is a function of a normalized performance indicator$X$, which measures the current performance of each sector relative to its optimal value:

$$\underline{S} = f(\underline{X}). \tag{2}$$

A portion of the generic purchases made by each sector are assumed to be nondeferrable, meaning that they will not be reattempted later if operational disruptions interfere with their timely execution. Other purchases may be reattempted. The "function" $f()$ is in general nonlinear and path-dependent, and is specified by the dynamic model of the sector.

4.2. *Solution heuristic*

Figure 4 shows the sequence diagram to find optimal α_{Pj} when the power infrastructure has the loss of power generation capacity L_{p}. The required procedures to find the solutions are as follows:

Step 1. Detect the loss of power generation capacity L_{p} due to the disruption or damage of power infrastructure. For example, $L_{\mathrm{p}} = 0.3$ means that 30% of power generation capacity is lost.

Step 2. Calculate available power production after the disruption, CI_{P}.

Step 3. Choose $\alpha_{\mathrm{p}j}$ $(0 \leq \alpha_{\mathrm{P}j} \leq 1)$, provide allocated power, $\alpha_{\mathrm{P}j} \times D_{\mathrm{p}j}$ $(j = \mathrm{R, C, I, T})$ to each economic sector j. Here, $CI_{\mathrm{P}} = \sum \alpha_{\mathrm{P}j} D_{\mathrm{P}j}$.

Step 4. Calculate $R_{\mathrm{pI}}, R_{\mathrm{pC}}, R_{\mathrm{pT}}$ and LA from economic sector simulators. Relative available power $R_{\mathrm{p}j}$ is presented as a value from zero to one. One means the electric power sector can fully satisfy corresponding power requests of the economic sectors and other infrastructures. The calculation accounts for backup power generation, battery or alternative power sources of each economic sector. For example, $R_{\mathrm{pI}} = 0.8$ means that the industrial sector only has enough power to satisfy 80% of industry power requests. $R_{\mathrm{pI}} = 0.8$ is input to the corresponding infrastructure subsystem (petroleum and natural gas in our study). The residential sector provides the work forces to all infrastructures. It represents labor availability as a value from zero to one. Insufficient power supply to residential sector will decrease the labor availability not directly but due to transportation and other delays.

Step 5. Using given $R_{\mathrm{pI}}, R_{\mathrm{pC}}, R_{\mathrm{pT}}$ and LA, determine each availability of critical infrastructure materials/services CI_i $(i = \mathrm{f, g, w, c})$ and distribute them to economic sector simulators using each material/service market allocation algorithm.

Step 6. Calculate total economic revenues, $TER = \sum ER_i$ $(i = \mathrm{R, C, I, T})$

Step 7. Change $\alpha_{\mathrm{p}j}$ and repeat Step 3 to step 6 until the optimal TER value is found.

4.3. *Allocation algorithms*

In this study, we used two allocation algorithms: (i) a normal, market allocation algorithm; and (ii) a simulation-based, nonlinear optimization algorithm. The normal, market allocation algorithm is used when there is no disruption. Infrastructure service providers specified the algorithm, which uses supply curves and demand curves for each infrastructure. The supply curve for a particular infrastructure service may be unique to that infrastructure or it may be compounded from supply curves for other infrastructures. The supply curve for electric power, for example, is composed of supply curves for distinct generator classes (based on fuel type) as well as supply curves characterizing the willingness of connected regions to export power. Demand curves are generally specified to be horizontal, so that infrastructure customers are price takers. The specification of inelastic demand reflects the assumption that customers will be unable to significantly change their process or technology over the time frame of the simulation.

Whenever a disruption occurs in a certain infrastructure, it causes a shortage of service/materials. We use our simulation model to predict the extent of the shortage and its impact across the entire system. We use our optimization algorithm to determine how to deal with that prediction. This is essentially the role of the Decision Support System (DSS) in Fig. 4.

4.4. *More on the simulation model*

Our overall simulation model integrates models of the individual infrastructures shown in Fig. 4. Those that comprise the integrated critical infrastructure are built as SD models. Each model views the infrastructure as a supply chain system of materials and services. And each includes aggregate inventories and flows of materials/services at an appropriate regional scale.

Models of energy production, transmission, and distribution are at the core of the national infrastructure models. We have built separate models for electric power, natural gas, and petroleum. Each model captures the three critical processes required to deliver products and services: (i) acquisition of inputs; (ii) production of the energy commodity; and (iii) transmission and distribution to customers. We modeled inventories as stocks, which can be buffered to account for variations in supply and demand. We included constraints on the production capacity, storage capacity, and transmission capacity.

Whenever a disruption occurs, the interconnection of these models provides the potential to explore both

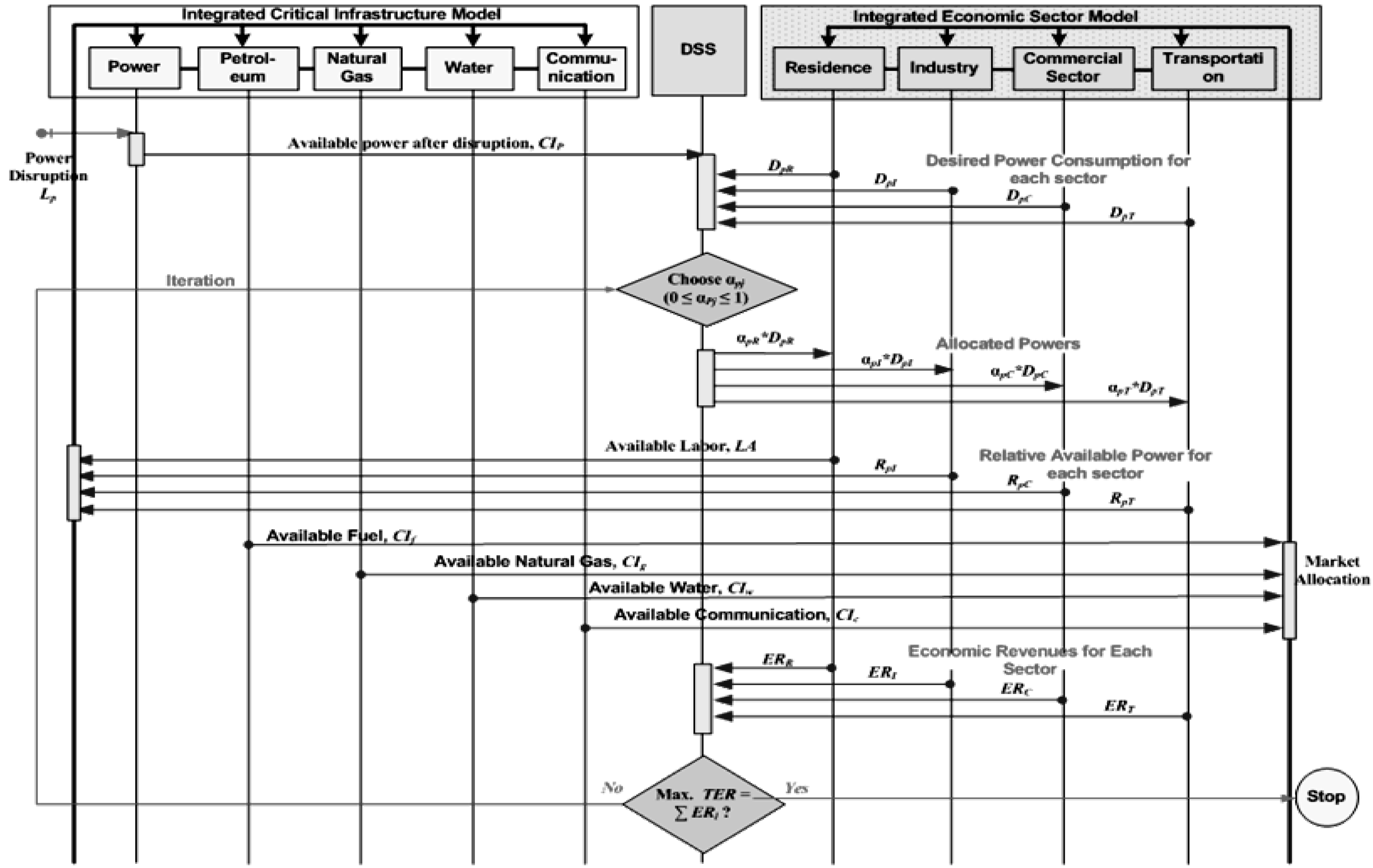

Fig. 4. The sequence diagram of power disruption and recovery scenario.

sector-specific economic impacts and broader economic impacts caused by propagation to other infrastructures or other sectors. Since our focus is on economic impacts, we have not considered other types of impacts in our initial version of the national model. For example, the electric power model tracks the available generation capacity in each defined region. This includes capacity: (i) serving load or providing reactive power; (ii) idle and available for dispatch; or (iii) completely unavailable. While the model includes transmission constraints as a limitation on inter-regional flow, it does not represent explicitly either the power grid itself or the processes required to ensure its stability. We plan to incorporate this capability in our later models.

The economic sectors have been included in our study because they drive indirectly most of the demand for infrastructure services. The economic sector demand is aggregated at the regional level for residential, commercial, and industrial consumers. The result of this aggregation is then added to the transportation demand to get the final demand. The role of these sector models is to define demands for the materials and services supplied by the basic infrastructures, capture the broader economic consequences of disruptions to these materials and services, and represent the interactions among these sectors to the extent that impaired performance in one sector, arising from infrastructure disruptions, may influence the economic activities and infrastructure demands in the other sectors.

4.5. *One Particular model*

Figure 5 shows a stock-and-flow model of the power-generation component of a power-infrastructure model. This model shows: (i) that state-level aggregates of power demand drive the regional power generation rates; and (ii) that imports can be used to bring in cheaper power or offset regional power shortfalls. Mathematical relationships between the variables in the stock-and-flow model (see Fig. 5) are provided in terms of difference or differential equations in Table 1 (rows 3–11), where rows 1 and 2 depict electricity regional divisions and technologies used to generate power, respectively. Variables are named so that their meaning can be inferred.

We note that these individual models can be run in either a stand alone or an integrated mode. This allows individual models to be tested and utilized without the necessity or complexity of running the entire national interdependency model.

5. Disruption experiments and results

In this work, we have conducted disruption experiments based on three scenarios. In scenario 1, we run the base scenario without any disruption: In scenario 2, a power disruption starting at time 60 hours and ending at time 108 hours. The loss of power generation capacity during the disruption is $L_{\mathrm{p}} = 0.4$, which means 40% of the power generation capacity is lost at time 60 hours. The market allocation algorithm for each critical infrastructure determined the allocation of each infrastructure materials/services. There is no intervention in the infrastructure materials/services markets by the government or other authorities. In scenario 3, we use the same conditions as in scenario 2 except that the allocation of power is determined by the DSS using a simulation-based nonlinear optimization algorithm, and allocation of other infrastructure materials/services is determined by the market allocation of each critical infrastructure.

Figure 6 shows a comparison of the change of total revenue, $\Delta(\sum ER_i)$, over the simulation runs for the three scenarios. In each case, the simulation started at time 0 and all the parameters were initialized based on historical data, which were collected from both government agencies and private industry. We used a time step, Δt, of 0.25 hours, and the run length of the SD simulation was 208 hours. Several interesting results were observed.

The overshoot in revenue in Fig. 6 between time 107 and time 117 is a consequence of the disruption that occurred prior to time 104 (see Fig. 9). During the disruption, some of the ordinary economic transactions do not occur. Instead, they accumulate during the disruption period and are completed when the infrastructure services are restored. The result is an increase in spending above the baseline level immediately following restoration for the residential sector.

The brief downturn in revenues of scenario 2 starting at time 107 in Fig. 6, also seen in the purchasing activity for the residential sector (in Fig. 7), is associated with the sudden surge in demand from the commercial sector at the time the outage ends (see the total electric power purchases for transportation in Fig. 8): This abrupt surge briefly diverts load from the other sectors, creating an additional shortfall in these sectors. This shortfall is relieved as generators are brought back on line. A similar behavior occurs at scenario 3.

The power delivered to the residential, commercial, and industrial sectors in the disrupted region for the three scenarios are shown in Figs. 9–12. The important distinction between the response of the market allocation scenario and the DSS scenario lies in the relative allocation to these three sectors. The DSS allocation favors the residential and commercial sectors, whereas the market allocation favors the industrial sector at the expense of the others.

The result reveals that scenario 3 outperforms scenario 2 in terms of the change in total economic revenues. After the disruption occurred at time 60 hours, the change in total revenues, $\Delta(\sum ER_i)$ of scenario 3 is always higher than that of scenario 2. In addition, the cumulative total economic revenues of the three scenarios during the disruption periods (from time 60 to time 108) are \$1106M, \$940M, and \$603M, respectively. In terms of the cumulative total economic revenues during the disruption period, DSS

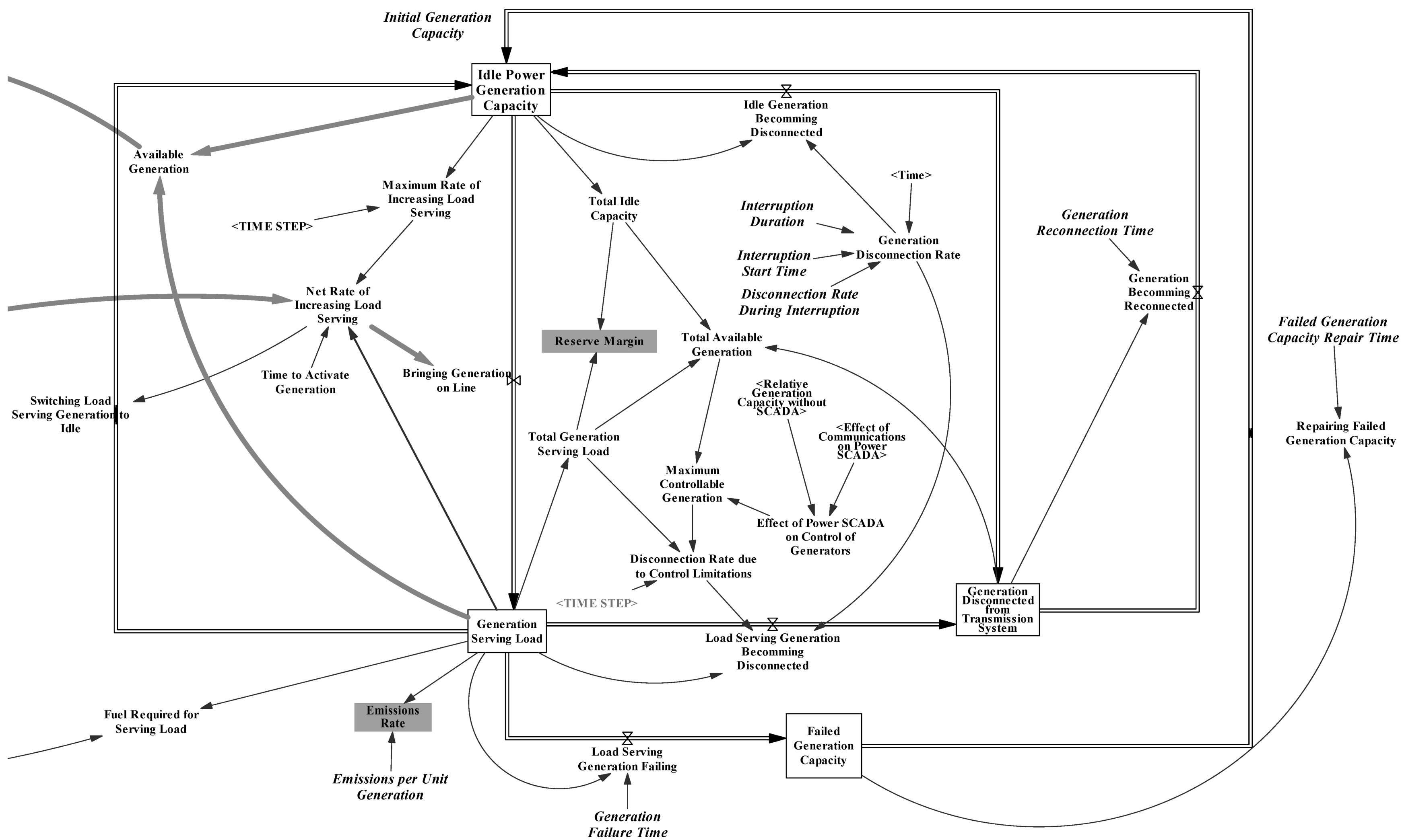

Fig. 5. SD model of the power generation system.

Table 1. SD model in Fig. 5 in terms of differential/difference equations

Difference or differential equations	*ID*
NERCRegion = ECAR, ERCOT, FRCC, MAAC, MAIN, MAPP, NPCC, SERC, SPP, WECC	1
GENTechnology = CoalGEN, NuclearGen, HydroGen, NGCMBSTGen, NGCCGen, NGSTGen, OilGen, DistillateGen	2
Total available generation [NERCRegion] = Total generation serving load [NERCRegion] + total idle capacity [NERCRegion] + Σ(generation disconnected from transmission system [NERCRegion,GenTechnology!]), unit = MW	3
Generation disconnected from transmission system [NERCRegion,GenTechnology] = ∫(idle generation becoming disconnected [NERCRegion,GenTechnology] + load serving generation becoming disconnected [NERCRegion,GenTechnology] − generation becoming reconnected [NERCRegion,GenTechnology]), unit = MW	4
Total generation serving load [NERCRegion] = Σ(generation serving load [NERCRegion,GenTechnology!]), unit = MW	5
Total idle capacity [NERCRegion] = Σ(idle power generation capacity [NERCRegion,GenTechnology!]), unit = MW	6
Generation becoming reconnected [NERCRegion,GenTechnology] = generation disconnected from transmission system [NERCRegion,GenTechnology]/generation reconnection time[NERCRegion], unit = MW/hour	7
Idle generation becoming disconnected [NERCRegion,GenTechnology] = idle power generation capacity [NERCRegion,GenTechnology] × generation disconnection rate [NERCRegion], unit = MW/hour	8
Load serving generation becoming disconnected [NERCRegion,GenTechnology] = generation serving load [NERCRegion,GenTechnology] × (generation disconnection rate [NERCRegion] + disconnection rate due to control limitations [NERCRegion]), unit = MW/hour	9
Generation serving load [NERCRegion,GenTechnology] = ∫(bringing generation on line [NERCRegion,GenTechnology] − load serving generation becoming disconnected [NERCRegion,GenTechnology] − load serving generation failing [NERCRegion,GenTechnology] − switching load serving generation to idle [NERCRegion,GenTechnology]), unit = MW	10
Idle power generation capacity [NERCRegion,GenTechnology] = repairing failed generation capacity [NERCRegion,GenTechnology] − bringing generation on line [NERCRegion,GenTechnology] − idle generation becoming disconnected [NERCRegion,GenTechnology] + generation becoming reconnected [NERCRegion,GenTechnology] = switching load serving generation to idle [NERCRegion,GenTechnology], unit = MW	11

(scenario 3) outperforms the market algorithm of power (scenario 2) by 16%. Therefore, based on the results of the experiment, market intervention in the critical infrastructure may be necessary in the case of disruptions or damages in order to minimize global economic impact.

The DSS allocation is based on an explicit minimization of economic loss. It should not, by design, lead to larger losses than any other allocation scheme having the same flexibility regarding timing of the allocation. The market allocation does not include global information about

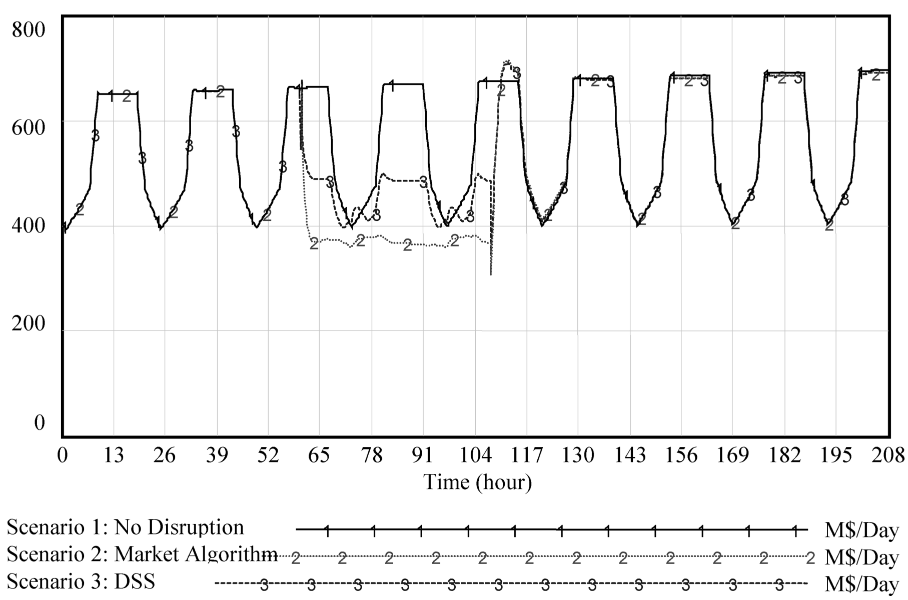

Fig. 6. Comparison of the results obtained using various policies.

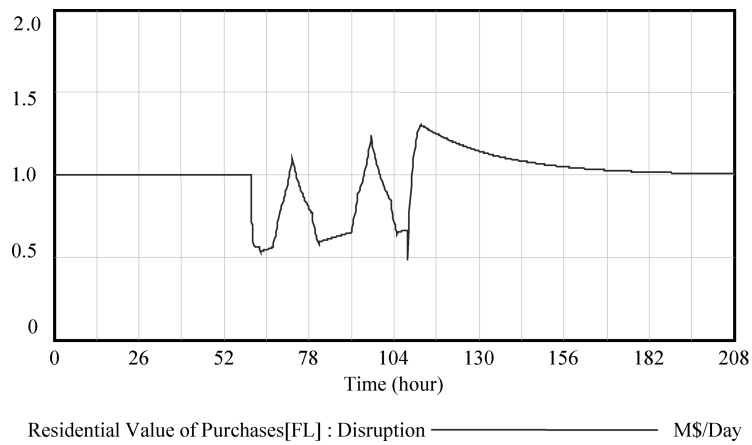

Fig. 7. Purchases transaction in the residential sector for scenario 2.

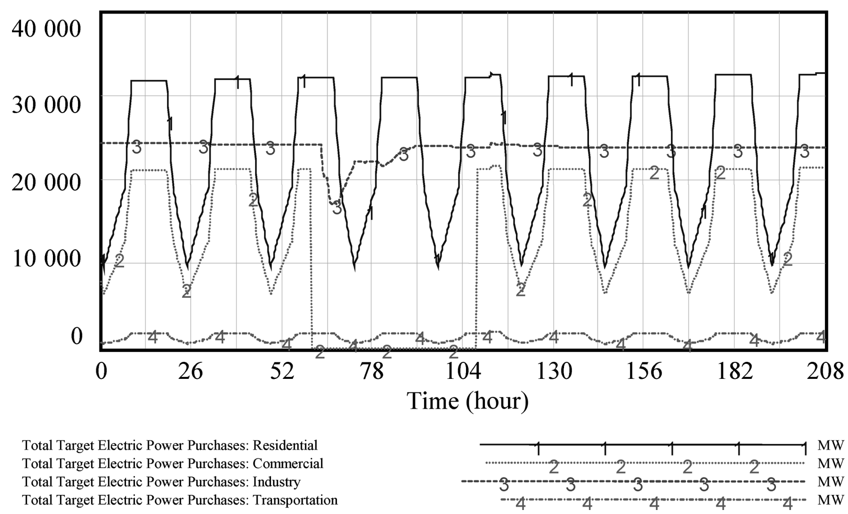

Fig. 8. Total target electric power purchases for scenario 2.

the larger economic ramifications of a particular allocation. Such information would ideally be reflected in the demand curves for the various sectors. In the model evaluated here the demand curves are exogenous and are not derived by consideration of substitutes and opportunity costs. Even if the model was extended to consider these factors, there is a basic limitation to the market allocation in that it is predicated on the local information available to each of the market participants: there is no reason to expect this allocation to achieve the global minimum of economic loss, which the DSS allocation is formulated to identify.

In Fig. 6, the DSS scenario also avoided loss of revenue during night-time hours and the market scenario did not. As shown in the sectoral power acquisition graphs (Figs. 10–12), the market allocation scenario favors the industrial sector, which has no daily variability in total power demand, over the commercial and residential sectors, which have strong diurnal variations in demand. As a consequence the nightly reduction in demand by the commercial and residential sectors are used to meet a larger fraction of the industrial sector's demand. This allocation, however, is uneconomic in the sense that meeting the demands of the commercial and residential sector would have led to

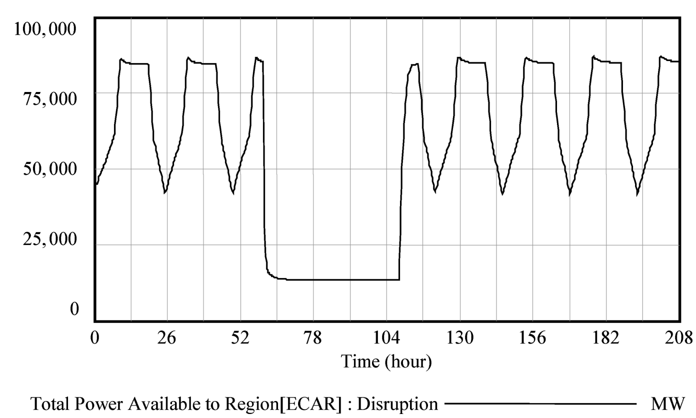

Fig. 9. Total power available to the region.

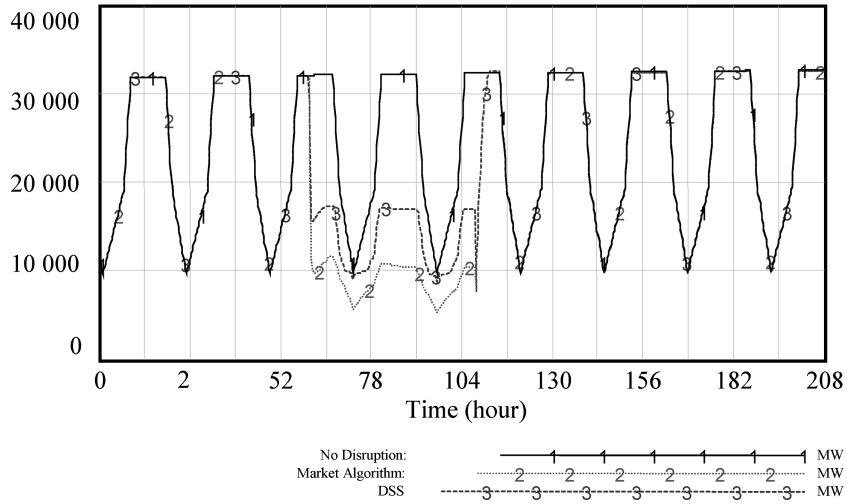

Fig. 10. Electric power acquired for the residential sector.

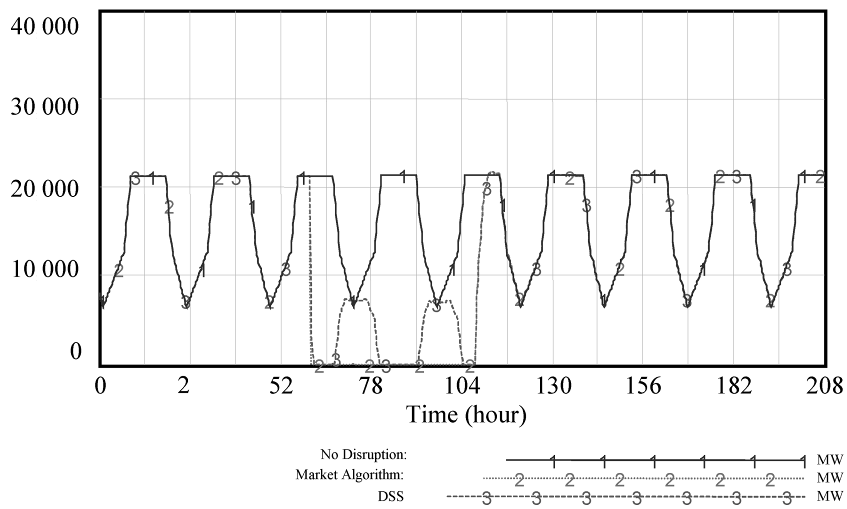

Fig. 11. Electric power acquired for the commercial sector.

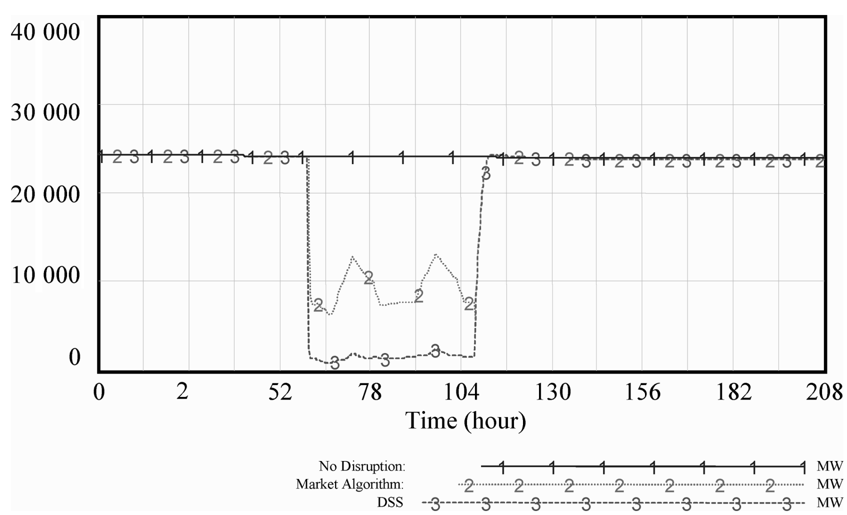

Fig. 12. Electric power acquired for the industry sector.

smaller economic losses. This opportunity is discovered and exploited by the DSS allocation, which nearly eliminates losses during the night-time hours by maintaining a small allocation to the industrial sector, and using the generation released the nightly reduction in residential demand to (nearly) satisfy the demands of the commercial sector.

6. Conclusions

In this work, we presented an innovative modeling and analysis framework to study the entire system of physical and economic infrastructures, where the framework is based on SD, functional modeling, and nonlinear optimization techniques. First, the SD approach allowed us to perform interdependency analysis among individual component infrastructures. Second, functional modeling using IDEFØ helped us to define data requirements and describe the exchange of information between the individual models. Also, we significantly benefited from the hierarchical nature of IDEFØ, where our modeling efforts in this study considered over 5000 variables and parameters. Third, nonlinear optimization enabled us to find the values for the control variables in SD simulation models such that an expected system performance from the SD simulation is optimized.

We demonstrated the potential use of the proposed framework to analyze, and propose a response for, a hypothetical disruption of an infrastructure. In the demonstration, we have used realistic models for many of the individual component infrastructures, outcomes of collaborative efforts among Sandia, other government agencies, private industry, and academia. The experimental results revealed that the proposed framework could reduce the devastating impact of disruptions.

Online synchronization between parameters of the SD model of the entire system of infrastructures and those of discrete-event models of individual infrastructures is left for future research.

7. Product disclaimer

Commercial software products are identified in this paper. These products were used for demonstration purpose only. This does not imply approval or endorsement by both Sandia National Laboratory and NIST nor that these products are not necessarily the best available for the purpose.

References

Anon, (2003) National strategy for the physical protection of critical infrastructures and key assets, available at http://www.whitehouse.gov/pcipb/physical.html. Accessed March 1, 2005.

Azadivar, F. and Tompkins, G. (1999) Simulation optimization with qualitative and structural model changes: a genetic algorithm approach. *European Journal of Operational Research*, **113**, 169–182.

Binder, T., Vox, A., Belyazid, S., Haraldsson, H. and Svensson, M. (2004) Developing system dynamics models from causal loop diagrams, presented at the 22nd International Conference of the System Dynamics Society, Oxford, UK.

Brown, T., Beyeler, W. and Barton, D. (2004) Assessing infrastructure interdependencies: the challenge of risk analysis for complex adaptive systems. *International Journal of Critical Infrastructures*, **1**(1), 108–117.

Davidon, W.C. (1959) Variable metric methods for minimization. A.E.C. Research and Development Report ANL-5990, Argonne National Laboratory, Argonne, IL.

Forrester, J.W. (1961) *Industrial Dynamics*, MIT Press, Cambridge, MA (currently available from Pegasus Communications, Waltham, MA).

Murtagh, B. and Saunders, M. (1998) MINOS 5.5 user's guide. Technical report SOL 83-20R, Stanford University, Stanford, CA.

Presidential Decision Directive 63, (1998) Available at http://www.ciao.gov. Accessed March 10, 2005.

Reid, R.A. and Koljonen, E.L. (1999) Validating a manufacturing paradigm: a system dynamics modeling approach, in *Proceedings of the 1999 Winter Simulation Conference*, IEEE, Piscataway, NJ, pp. 759–765.

Richardson, G. (1986) Problems with causal-loop diagrams, *Systems Dynamics Review*, **2**(2), 158–170.

Richardson, G. (1997) Problems in causal loop diagrams revisited. *Systems Dynamics Review*, **13**(3), 247–252.

Rinaldi, S., Peerenboom, J. and Kelly, T. (2001) Identifying, understanding, and analyzing critical infrastructure interdependencies. *IEEE Control System Magazine*, **21**, 11–25.

Robinson, S.M. (1972) A quadratically convergent algorithm for general nonlinear programming problems. *Mathematical Programming*, **3**, 145–156.

Sterman, J.D. (2000) *Business Dynamics: Systems Thinking and Modeling for a Complex World*, McGraw-Hill, New York, NY.

Wolfe, P. (1962) The reduced-gradient method. Internal resport, The Rand Corporation, Santa Monica, CA.

Biographies

Hyeung-Sik Jason Min is a Senior Member of Technical Staff in the Critical Infrastructure Modeling and Simulation Group at Sandia National Laboratories. He received his Ph.D. in Industrial Engineering from Purdue University. Prior to joining Sandia National Laboratories, he worked as a NRC post-doctoral research associate at the NIST. His current research interests include multi-paradigm modeling and simulation, hybrid and distributed simulation for applications with various scales and complexities in areas of manufacturing and homeland security. He is currently a member of INFORMS and IIE.

Walter Beyeler is a Principal Member of Technical Staff at Sandia National Laboratories in Albuquerque NM. His general background is in modeling and decision analysis related to diverse engineered and natural systems. Current work includes agent-based modeling of infrastructures and infrastructure interactions using complexity theory and complex adaptive systems. Past experience at Sandia includes modeling analyses of groundwater flow and transport, statistical and geostatistical data analysis, and development and application of uncertainty/sensitivity and decision support techniques.

Theresa Brown is a Principal Member of Technical Staff in the Infrastructure Simulation and Modeling Department at Sandia National Laboratories. As Project Leader for the National Infrastructure Simulation and

Analysis Center (NISAC) she is responsible for the technical work of the 12 modeling, analysis, visualization, knowledge management and computational platform teams. Her technical expertise is in conceptual model development and decision-making under uncertainty using vulnerability and risk analyses and probabilistic performance assessments. She has a Ph.D. in Geology from the University of Wisconsin–Madison, an M.A. in Geology from the University of Texas at Austin and a B.S. in Earth Science and Secondary Science Education from Adams State College.

Young-Jun Son is an Associate Professor of Systems and Industrial Engineering at The University of Arizona. He is an Associate Editor of the *International Journal of Modeling and Simulation* and the *International Journal of Simulation and Process Modeling*. He is a recipient of the Society of Manufacturing Engineers 2004 M. Eugene Merchant Outstanding Young Manufacturing Engineer Award, and also the Institute of Industrial Engineers 2005 Outstanding Young Industrial Engineer Award. He has authored or co-authored over 60 publications in refereed journals and conferences, primarily on developing the new field of distributed federation of multi-paradigm simulations and expanding the field of computer-integrated control to encompass the extended manufacturing enterprise.

Albert Jones has spent the last 25 years at the National Institute of Standards and Technology (NIST). Currently, he manages the Enterprise Systems group, which focuses on supply chain integration. Previously, he was Deputy Director of the Automated Manufacturing Research Facility at NIST. His research interests include complex systems, next generation control systems, simulation, and scheduling systems. He has published numerous journal and conference papers in these areas. He is on the Engineering Advisory Boards at Morgan State University and Loyola College. Before coming to NIST, he held faculty positions at Loyola College and Johns Hopkins University.